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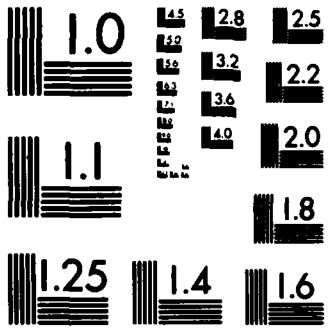
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James H. Howard, Jr.

ONR Contract Number N00014-83-K-0481

Work Unit Number R&T 4424182

Technical Report ONR-86-25

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Considerable recent physiological and psychophysical evidence suggests that the visual system operates as a series of independent channels or analyzers, each sensitive to image structure at a different spatial scale. In this view, image structure is processed separately at different scales by the various channels. Several individuals have argued that the broad, low-frequency channels respond to global or Gestalt properties of an image and are important in early processing--for instance, during an initial glance at an image. In contrast, the high-frequency channels are sensitive to local detail and are important in later visual

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processing when attention has been focused on a particular aspect of the image. Two experiments investigated the ability of human observers to detect and recognize simple objects in visual images. Prior to presentation, the images were transformed by spatial frequency filters to emphasize the global- (low spatial frequencies), local- (high spatial frequencies) or intermediate- (mid spatial frequencies) scale structure. Four categories of top-view ship hulls were synthesized for the experiments. In the first experiment separate groups of observers made both detection (which quadrant of the display contained a ship?) and recognition (which of the four ships occurred?) judgments. In the second experiment, observers also selected the filter condition to be displayed on each trial prior to the detection or recognition response.

The results showed that, as expected, filter condition had a large effect on recognition performance with the unfiltered images recognized better than the high-frequency images which in turn were recognized better than both the mid- and low-frequency images. As predicted, and in contrast to the recognition data, the low-frequency images led to better detection performance than either the mid- or the high- frequency conditions. The low-frequency images were also more easily detected than the unfiltered images. However, when permitted to select a filter condition to observe in the second experiment, observers did *not* select the optimal unfiltered image for recognition, but selected the original and the high-frequency images equally often. In contrast, for detection observers consistently selected the optimal low-frequency images. The observer selection results indicate that individuals are not always able to anticipate the viewing conditions which will lead to optimal perceptual performance. The implications of these results for human/computer interaction in image processing are discussed.

It is obvious that the physical world is highly structured and that this structure exists at many levels. For example, the surfaces of objects in an office possess a gross or very global structure as in the outline form of the desk, bookshelves or computer terminal. On the other hand, these objects may also be characterized in terms of their more detailed, local structure as in the shapes of individual books, desk drawers or the terminal keyboard. When light is reflected from these surfaces to create an image, intensity variations over the two image dimensions capture many aspects of this three-dimensional structure. The most fundamental problem of spatial vision is to understand the way in which this information is used to interpret the visual world. Although psychologists and others have been interested in this very basic perceptual problem for many years, a full understanding has remained elusive.

Computer vision theorists have argued recently that to be successful visual analyses must take place across several levels of image scale, with each level contributing to the overall understanding of the objects in the image (Marr, 1982; Yuille & Poggio, 1983; Crowley & Sanderson, 1984). Interestingly, considerable physiological and psychophysical evidence suggests that the mammalian visual system may operate in this fashion (Sekuler, 1974). Specifically, the visual system contains a series of independent channels or analyzers, each sensitive to image structure at a different scale (Julesz & Schumer, 1981). These channels are thought of as broadly-tuned spatial frequency filters (Julesz, 1980), bar detectors of varying widths or sizes (Macleod &

Rosenfeld, 1974), or zero-crossing filters of different bandwidths (Marr, 1982). In this view, image (and hence object) structure is processed separately at different scales by the various channels. For example, the global structure of an image is extracted independently of any local detail (or vice-versa), and some have argued that this global anlysis may actually precede or dominate the more local analysis (Hughes, Layton, Baird, & Lester, 1984).

With the increasing evidence for the existence of these channels, research has turned to the question of their role or function in vision. Several individuals have argued that the broad, low-frequency channels respond to global or Gestalt properties of an image and are important in early processing--for instance, during an initial glance at an image (Broadbent, 1977; Julesz, 1980). In contrast, the high-frequency channels are sensitive to local detail and are important in later visual processing when attention has been focused on a particular aspect of the image. Despite the growing popularity of this view, relatively little experimental work has explored the implications of these hypothesized differences for visual perception. The experiments reported in this paper address this question by investigating the ability of human observers to detect and recognize simple objects in visual images. Prior to presentation, the images are transformed by spatial frequency filters to emphasize the global- (low spatial frequency), local- (high spatial frequency) or intermediate- (mid spatial frequencies) scale structure. The results support the hypothesis that spatial scale plays an important role in the detection and recognition of objects in visual imagery.

Evidence For Visual Channels

In 1843 Ohm proposed that the human auditory system can decompose a complex sound into its elementary frequency components (cited in Julesz, 1980). Ohm's Acoustical Law--as this proposal is known--paved the way for Helmholtz, von Bekesy, and ultimately Fletcher, to develop a view of the auditory system which is based on a set of broadly-tuned filters, called critical bands, each of which responds to only a subset of frequencies in the audible spectrum. These filters, or channels, form the basis of much of contemporary auditory theory. The argument that they exist is intuitively compelling since it is common experience to hear the tonal components when listening to a complex sound such as a musical chord.

Although Young proposed the existence of separate channels for color vision in the early 1800's, the analogous concept of independent channels in human spatial vision is a relatively recent proposal. Campbell and Robson (1968) were the first to suggest that vision may be based on a set of spatial frequency analyzers each of which responds to only a narrow range of spatial frequencies. This proposal suggests, unintuitively, that at some level in the visual system, a complex pattern may be decomposed into a finite set of simpler, periodic intensity patterns. Despite its lack of intuitive appeal, this basic idea has gained wide acceptance in recent years with significant support from both physiological and psychophysical findings (see reviews by Sekuler, 1974; DeValois & DeValois, 1980; Julesz & Schumer, 1981).

One implication of the multichannel model of spatial vision is that overall spatial sensitivity, as measured by the modulation transfer function (MTF) for example, reflects the envelope of a number of individual sensitivity curves. Two basic questions follow. First, how many individual channels exist, and second, what is the underlying sensory mechanism for each channel? Both questions are addressed in a model proposed by Wilson and Bergen (1979). The model proposes that four broadly-tuned, size-sensitive mechanisms exist at each point in the retina. Furthermore, the size of these units increases linearly with eccentricity on the retina, and the composite sensitivity at any point results from probability summation across the four units. The proposed units resemble the on-center, off-surround retinal cells described by Kuffler (1953), with a sensitivity profile characterized by a difference of Gaussian distributions--one narrow and positive (excitatory) and the other broad and negative (inhibitory). Although more recent work has reinterpreted these basic units to be zero-crossing (Marr, 1982) or other (e.g., Daugman, 1983) filters rather than size-sensitive units, the distinction between these interpretations is not especially important for this paper. The important point for the present argument is that at least four broadly-tuned visual channels seem to exist which respond to information at different spatial scales. Whether these channels reflect size sensitive units, zero-crossing filters, or spatial frequency filters is not of concern here.

Much of the psychophysical evidence for the existence of spatial channels is based on experiments with one-dimensional sinusoidal grating patterns. In this type of pattern, intensity varies sinusoidally in one dimension with this variation extended redundantly across the second dimension. Surprisingly few studies have used two-dimensional patterns as may occur in realistic imagery. Fortunately, in cases where complex imagery such as faces (Harmon & Julesz, 1973; Fiorentini, Maffei, & Sandini, 1983), scenes (Caelli, 1983) or complex textures (Ginsburg, 1978; Caelli, 1982) have been used, the results have been consistent with the multichannel model. The imagery investigated in the present experiments depicted simple top-view intensity profiles of simulated ship hulls on uncluttered backgrounds.

The Role of Channels in Spatial Vision

As the evidence for the existence of multiple, scale-sensitive channels has accumulated, increasing numbers of investigators have speculated on their possible role in spatial vision. Most discussions of this issue have pointed out that one should be cautious in assuming that the channels literally perform a spatial Fourier analysis which could lead to a reconstruction from the orthogonal components. The small number of channels and two-octave bandwidths proposed are too limiting for this purpose (Julesz, 1980). Rather, most speculation on the role of these channels has involved some kind of underlying attentional mechanism.

In an early proposal, Broadbent (1977) identified two gross stages in human visual analysis, an early, relatively automatic preattentive stage and a subsequent active, attentive analysis. In his view, the early processing is based on global information and serves to segregate "...detailed stimuli into bundles or segments that can be attended to or rejected as a whole" (p. 112). In contrast, the later processing is based on the detailed information in the image. He speculated further that the visual mechanism which accomplishes this analysis could very well be the scale-sensitive channels described in the previous section of this report.

A more complete attentional hypothesis has been developed by Julesz (Julesz, 1980; Julesz & Papathomas, 1984). He proposes that the spatial channels serve as a kind of "perceptual zoom lens" that permits an image to be analyzed at any of a number of levels. For example, "...a low-frequency channel will discard fine details and thereby emphasize the overall layout of the entire picture. A high-frequency channel brings the local details into prominence at the expense of the large-scale regions and structure" (1980, p. 309). He points out that the assumed two-octave bandwidths proprosed for the filters would permit three "lenses" at low- (.5-2 cycles/degree of visual angle), mid- (2-8 cycles/degree), and high- (8-32 cycles/degree) spatial scales. Although some controversy exists (e.g., Gellatly, 1983), Julesz and Papathomas (1984) have recently presented some demonstrations which support what they term a strong version of this attentional hypothesis--that the spatial channels function in attention <u>and</u> that the observer can exert control over the specific channel that will be dominant at any

instant.

Related to this are some recent discussions of the relation between spatial scale and the traditional Gestalt distinction between "figure" and "ground." Julesz and his colleagues (Julesz, 1978; Julesz, 1980) have suggested that the "figure" portion of an image receives a more detailed analysis than the "ground" portion. Presumably, this would involve high- and low-frequency channels for the "figure" and "ground," respectively. This was supported in a simple, but informative visual detection experiment by Wong & Weisstein (1983). Prior to presenting a stimulus, observers were asked to fixate an ambiguous goblet/faces image and to indicate when a designated portion of it (e.g., goblet) was seen as figure. In this way a small test line could be presented in either a figure or a ground region of the display. Two line targets of different spatial frequency content were used, a sharply defined line which had a relatively broad spectrum, and a blurred line which had a markedly peaked spectrum with most of its energy at lower frequencies. In other words, the sharp target had considerably greater high frequency content than did the blurred target. The results of their experiments revealed that the high spatial frequency target was more accurately detected in a region perceived as "figure" whereas the low-frequency target was more accurately detected in a "ground" region. They concluded that the global character and the rapid response time (see following section) generally attributed to low spatial frequency channels make them well suited for processing image ground (Wong & Weisstein, 1983). This suggests that the subjective state of attending to a spatial

region--the figure--selectively activates the high detail channels. These results are consistent with the attentional hypothesis outlined earlier. Unfortunately, relatively few studies have actually examined the hypothesis empirically as in this case.

Global Precedence and Low-Frequency Dominance

An important aspect of Broadbent's discussion of the role of spatial channels in attention is the notion that the global (low-frequency) analysis temporally precedes the local (high-frequency) analysis. This refers to a recurring theme in recent visual information processing studies, and is sometimes referred to as the global precedence effect (Navon, 1977; Ward, 1982; Hughes, Layton, Baird, & Lester, 1984). As implied by the title of Navon's original 1977 article, the global precedence effect asserts that in a relative sense the global information in an image--"the forest"--will be processed before the local information--"the trees." Although the proposal is not without controversy (see for example, Miller, 1981; Ward, 1982), most agree that global dominance is often observed.

In a recent study, Hughes and his colleagues have examined the effect under a variety of conditions. They present the argument that local and global processing occurs concurrently and that the presence of global cues can serve to retard the processing of local information. They also speculate that global precedence may result from asymmetric neural inhibition between the local and global spatial frequency channels (Morrone, Burr, & Maffei, 1982 cited by Hughes et al, 1984). It is also interesting to note that Wilson &

Bergen (1979) attribute different temporal response characteristics to their four size-sensitive mechanisms. These findings are reminiscent of earlier work which revealed two types of temporal response in spatially-sensitive retinal cells. As Braddick, Campbell, and Atkinson (1978) summarize, "The X- or sustained cells show linear spatial summation, small receptive fields (and hence a good response to high spatial frequencies but a poor response to low), and a sustained temporal response. The Y- or transient cells are spatially nonlinear and respond to lower spatial frequencies than X-cells in the corresponding retinal region." (p. 27). Although the implication of these cells in the attentional processes that Broadbent (1977) distinguished would be very speculative, it is of interest that known temporal response properties of spatial vision channels are consistent with the attentional hypothesis.

Experiment 1

The purpose of this experiment is to investigate the ability of human observers to detect and recognize simple two-dimensional visual objects under conditions where the low-, mid-, or high-spatial frequency content is dominant. The objects were four simulated top views of ship hulls distinguished by the presence of one or two deck houses and by the presence of square or circular upper deck structures. The research summarized in the preceding discussion suggests that spatial frequency should be of major importance in determining the detection and recognition performance achieved with the spatially filtered images. For example, since the visual cues which permit the four ships to be discriminated involve

relatively fine detail and hence, primarily high spatial frequencies (see method for a more complete discussion), recognition performance should be best when high-frequencies are dominant but difficult or impossible when this information is reduced as in the low- and mid-dominant conditions. On the other hand, the low frequency channels should play a primary role in detection and, therefore, the low-dominant conditions should lead to optimal detection performance. By a parallel argument, the mid- and high-dominant images should be relatively difficult to detect.

To summarize, according to the attentional hypothesis for the ship images employed here, the low-frequency dominant imagery should lead to poor recognition performance, but to very good detection performance. In contrast, the high-frequency dominant images should lead to good recognition performance, but relatively poor detection performance.

Method

Observers. Six paid undergraduate volunteers served as observers in the experiment. Two served in both the detection and recognition tasks, two in only the detection task, and two in only the recognition task. All of the participants had normal or corrected-to-normal vision.

Apparatus. Image preparation, control of experimental events, and data analyses were carried out on a general purpose laboratory computer (Digital PDP-11/23). This computer served as a controlling host for a Gould Imaging and Graphics IP8400 image processing system

which was used for on-line image processing, storage, and presentation. Participants were seated in a darkened room and viewed the test imagery on a high-resolution, 9 in (22.9 cm) diagonal, monochrome monitor (Cohu Model DM 9/C) at a viewing distance of 122 cm. The image was displayed with a resolution of 256 by 256 8-bit pixels in one quadrant of a 512 by 512 pixel display. Participants entered their responses on a standard terminal keyboard, and verbal feedback was displayed on the monitor by means of the IP8400 alphanumeric generator.

Imagery. Preparation of the test imagery involved several steps. Initially, top-view images of the four ships were created by varying a two dimensional intensity profile as shown in Figure 1. Ships A and C are characterized by a split deck house with square and circular upper deck structures, respectively. Ships B and D have a single deck house with square and circular upper deck structures, respectively. It is clear from Figure 1 that the differences among the four ships are based on a small number of pixels and hence on relatively high spatial frequencies. The gap distinguishing the split and full deck house is six pixels (.088 degree of visual angle at the 4 ft viewing distance), and the difference between the circular and square deck structures is three pixels on the diagonal (.044 degree).

Once the images were constructed, three transformed versions of each ship were created to emphasize low-, mid-, and high-spatial frequencies. Each ship image was Fourier transformed using an FFT alogrithm (see Gonzales & Wintz, 1977). The frequency domain representation of each ship was then multiplied by circular low-pass

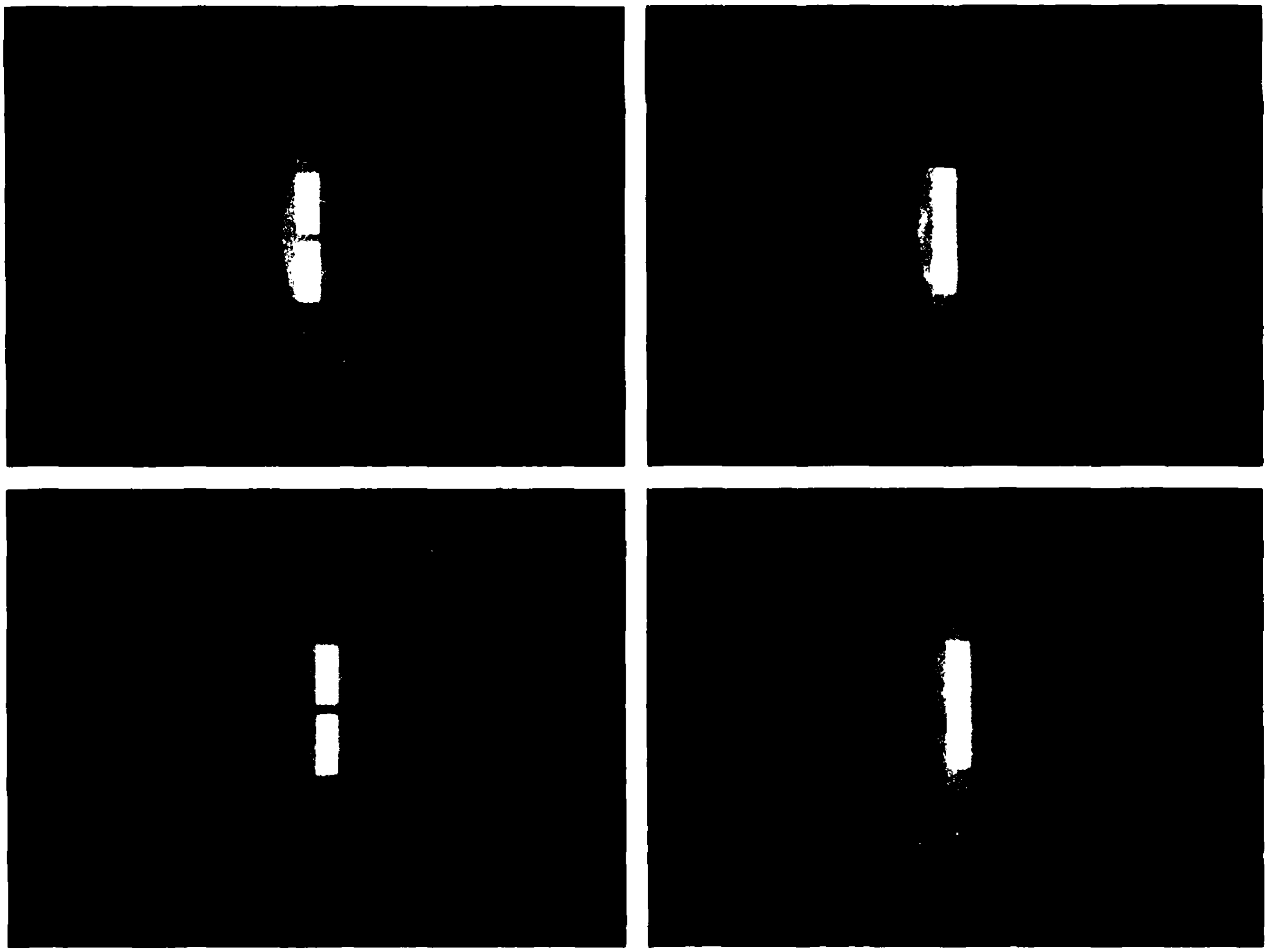
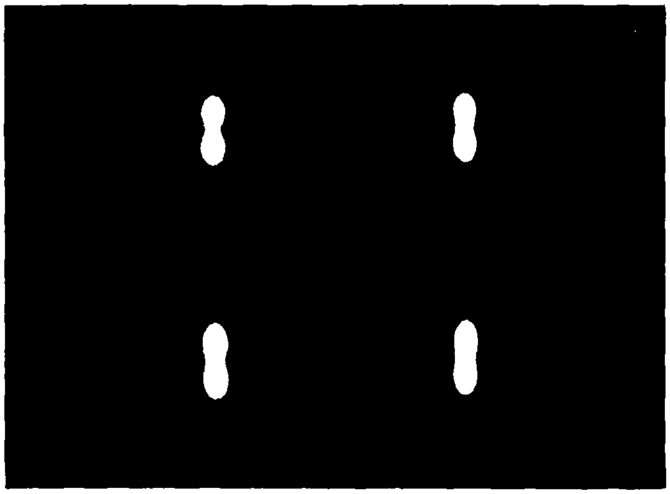


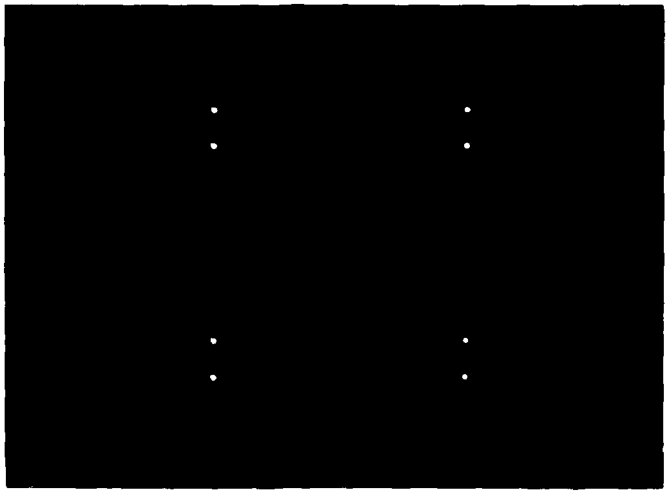
Figure 1. Unfiltered top-view images of simulated ship hulls. Ship A appears in the upper left, ship B in the upper right, ship C in the lower left, and ship D in the lower right.

and band-pass "pill-box" filters with two-octave bandwidths. The low-pass filter was centered at 1 cycle/degree (0-8 pixels), the mid-pass filter at 5 cycles/degree (9-32 pixels), and the high-pass filter (actually a band-pass filter) at 21 cycles/degree (33-128 pixels). The resulting data were then inverse transformed back into the image domain for presentation. Although two-octave filters were used, the resulting displayed imagery had somewhat broader bandwidths because of the mapping used to display the transformed images. The resulting images had dominant information in the low, mid, and high spatial frequency regions. These images are shown in Figure 2.

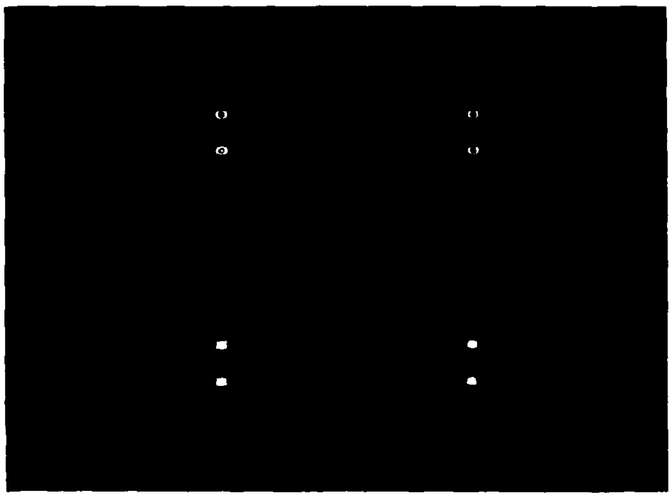
Finally, the transformed and original ship images were adjusted to have equivalent mean luminance when displayed on the calibrated monitor as measured by a Photo Research Model 502 spot photometer. Pilot experimentation was carried out to establish presentation durations and intensities which would yield acceptable performance levels in the detection and recognition tasks, that is, with neither floor nor ceiling effects in either task. For recognition, a display time of approximately 132 ms was used with a mean display luminance of approximately 15.52 cd/m^2 . For detection, the images were presented for a single frame time of approximately 33 ms and observers viewed the monitor through neutral density filters to achieve an overall reduction in display luminance of 4.3 log units from the recognition level.



Low-pass Condition



Mid-pass Condition



High-pass Condition

Figure 2. Spatial frequency filtered images of simulated ship hulls. Within each filter condition ship A appears in the upper left, ship B in the upper right, ship C in the lower left, and ship D in the lower right.

Procedure. Prior to beginning the experiment, observers read instructions which explained the task. For detection they were told that a ship would occur on every trial and that only the quadrant in which it appeared was important--its identity could be ignored. Conversely, for recognition they were told to ignore the quadrant of presentation and to identify the ship. In the latter case, a sketch of the four ship types was provided. Testing took place in a darkened room and a ten-minute dark adaptation period preceded the detection sessions. Individual trials were similar for the detection and recognition sessions and began with a 500 ms presentation of a cross-hair fixation which divided the display into quadrants. Following this the cross-hair was replaced by one of the 4 ship images selected randomly. This remained visible for 33 ms for the detection trials (1 video frame time) or 132 ms for the recognition trials (4 frame times). Observers entered their response on a standard keyboard. For recognition trials, verbal feedback regarding the correct response was displayed on the monitor for 2 s. No feedback was provided on the detection trials. The duration of the inter-trial-interval varied depending on the time required to obtain the next image from a disk file, but was approximately 1.5 s. Observers completed 384 trials per session (6 occurrences of the 4 ships by 4 filter conditions by 4 quadrants) for 5 sessions totalling 1920 trials per individual.

Results and Discussion

Overall recognition performance. A mean percentage correct was calculated for each condition for each of the four observers across the five experimental test sessions. These overall means are presented in Figure 3 for the three filtered and the unfiltered images. These data were submitted to a three-way (filter condition by ship by day) repeated measures ANOVA. Several findings were of interest. First, as expected, a significant main effect of filter was obtained, $F(3,9)=26.56$, $p<.001$, with no significant interactions between filter and any of the other variables. A post-hoc analysis of these differences with Duncan's New Multiple Range Test revealed that performance was significantly better for the unfiltered images (69%) than for any other condition, that the high-pass imagery was recognized more reliably (45%) than the mid- and low-pass cases (31% and 32%, respectively), and that the mid- and low-pass cases were not reliably different from each other.

Second, no main effect of ship occurred (43%, 45%, 43%, and 45% for ships A, B, C, and D, respectively), $F(3,9)<1.0$, and no significant interactions were obtained between ship and any other factor. This result indicates that no single ship had unique or idiosyncratic properties which may otherwise limit interpretation of the filter effect.

Third, a reliable main effect of day was observed, $F(4,12)=6.87$, $p<.01$, with overall performance increasing across the first four days and leveling off by the fifth day (37%, 40%, 45%, 49%, and 50% for the five days, respectively). Although not specifically predicted, a practice effect of this type is not unexpected. The further finding that no reliable interactions

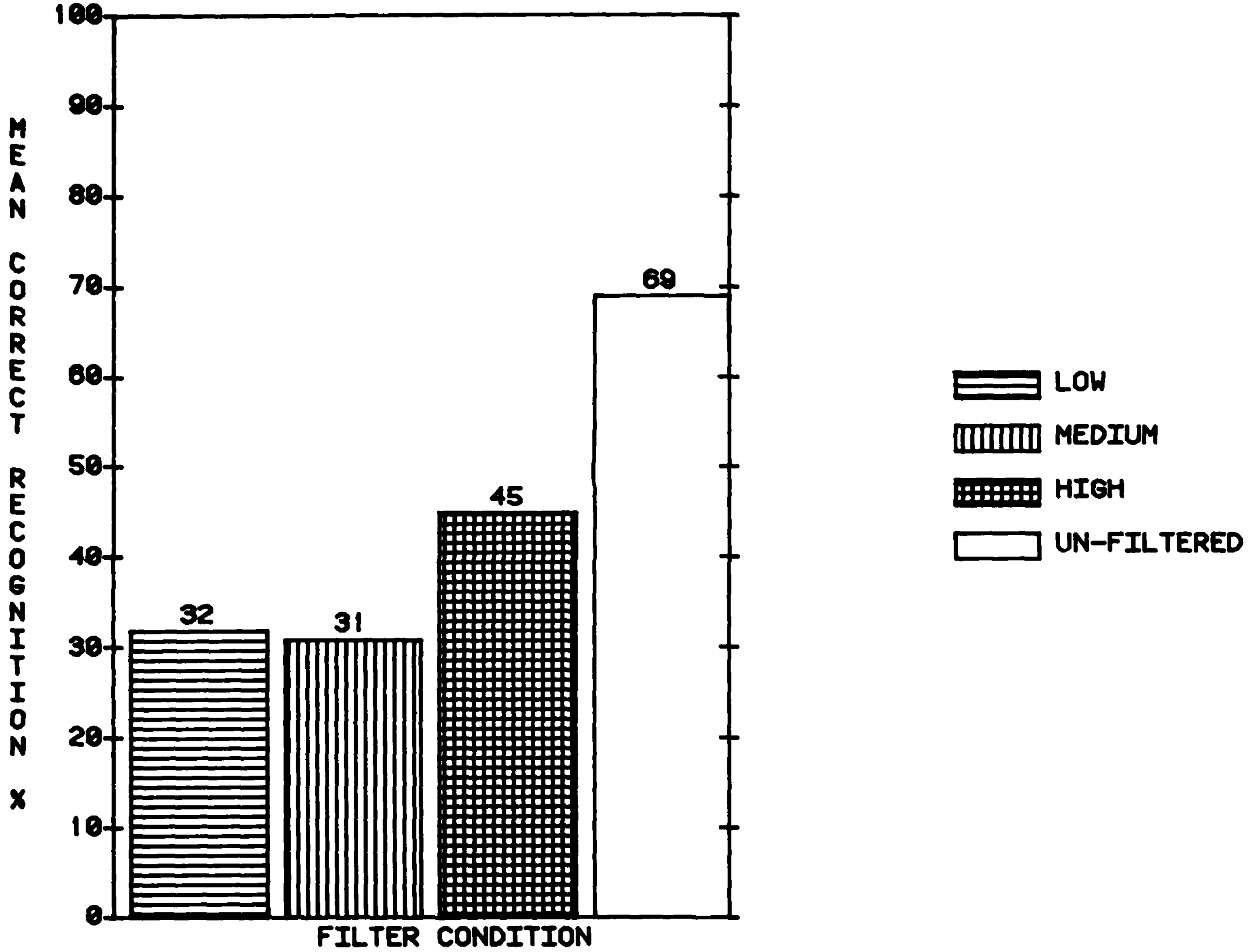


Figure 3. Overall mean percent correct recognition for each of the four filter conditions, Experiment 1.

occurred between day and any other factor indicates that practice simply led to improved performance, regardless of the viewing condition.

Response bias in recognition. The above findings are consistent with our predictions. It would be difficult to account for the observed pattern of results by response bias alone. Nevertheless, overall performance level may reflect response bias tendencies as well as actual observer sensitivity to the image attributes.

A prelimary analysis was carried out to examine the recognition data for evidence of response bias. This analysis involved compiling the frequency of each recognition response for each filter condition and observer. Any tendency to favor a particular response regardless of the actual ship that was presented would indicate the presence of response bias. These frequencies were analyzed by a two-way, repeated measures ANOVA (filter condition by ship). No significant main effects or interactions were obtained. Hence, there was no systematic bias. Despite this, a detailed examination of individual data did suggest a slight response bias for one observer. Specifically, this individual displayed a tendency to indicate ship A or ship B (both with square deck structures) whenever an unfiltered or high-frequency image occurred (61% vs. 39%) and to indicate ship C or ship D (circular deck structures) whenever a mid- or low-frequency image occurred (65% vs. 35%). This suggests that the presence of high spatial frequencies led this individual to "see" a ship with sharp features (the square deck structures) rather than one with smooth features. Nevertheless,

this tendency was not sufficiently strong to play a major role in the overall data.

<u>Analysis of recognition confusions</u>. The previous analyses have shown that observers recognize the unfiltered and high-frequency ships more reliably than they do the mid- and low-frequency ships, and that this result cannot be attributed to response bias. Additional analyses were carried out on the types of confusions which actually occurred to obtain more information about what aspects of the imagery made the mid- and low-conditions difficult. Two by two confusion matrices were derived for each individual and filter condition, one for the split/full deck house attribute and the other for the square/circular deck structures attribute. A response-bias free index of performance, d' (see Green & Swets, 1966), was then determined for each matrix by defining a hit as a split-deck category response (ships A or C) given that a split-deck occurred and a false alarm as a split-deck response when a full-deck actually occurred (ships B or D). Analogous definitions were used for the square/circular deck structures matrix.

A mean d' discrimination index was then determined for each filter and attribute by averaging across individuals. These means are shown in Figure 4. A two-way (filter by attribute), repeated measures ANOVA revealed reliable main effects of both filter, $F(3,9)=27.24$, $p<.001$, and attribute, $F(1,3)=27.24$, $p<.001$, as well as a significant filter by attribute interaction, $F(3,9)=5.90$, $p<.025$. As is evident in Figure 4, the filter effect obtained with these bias-free means mirrors that reported for the overall performance analysis (mean d's: unfiltered=2.18, high=1.04,

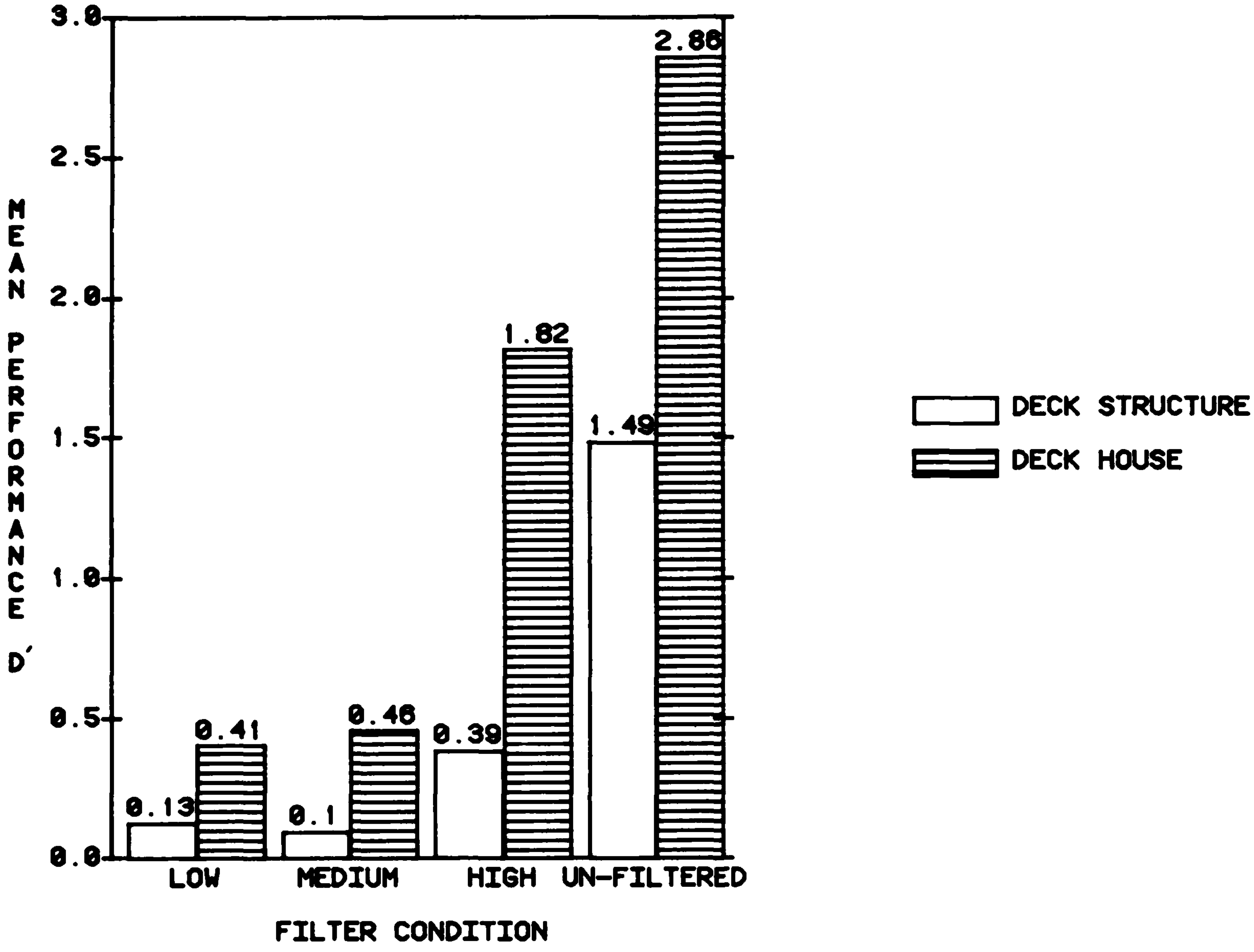


Figure 4. Overall mean $\underline{d}'$ values by deck-structure and deck-house attribute for each of the four filter conditions. The deck-structure data are shown without cross hatching, the deck-house data with cross hatching.

low=.27, and mid=.28). The main effect of attribute reflects a large performance advantage for the split/full deck discrimination (mean *d*'=1.39) over the circular/square structure discrimination (mean *d*'=.50). Furthermore, as seen in Figure 4, the reliable interaction indicates that this advantage occurred primarily for the unfiltered and high frequency images.

Recognition latency analysis. A mean response latency was determined for each condition and individual in the experiment. The results are shown in Figure 5. These data were analyzed by a three-way (filter condition by ship by day), repeated measures ANOVA. The analysis revealed a significant main effect of filter, $F(3,9)=5.82$, $p<.025$; no other main effects or interactions were significant at the .05 level. Inspection of Figure 5 suggests that the main effect of filter condition reflects a partitioning of the latencies into two sets, relatively fast for the low-frequency images (1394 ms), and relatively slow for the unfiltered, high- and mid-frequency images (overall mean of 2031 ms). A follow-up post hoc analysis with Duncan's New Multiple Range test confirmed this observation with reliable differences occurring across the slow and fast groups, but no reliable differences occurring within the slow conditions. Although individuals differed dramatically in their average response time (from 1442 ms to 2163 ms), each showed this pattern. These findings, coupled with the accuracy data, suggest that observers might have regarded the low-frequency images as a "lost cause" and responded relatively quickly whenever they occurred. On the other hand, a simple speed/accuracy tradeoff cannot account for the overall pattern of latencies because

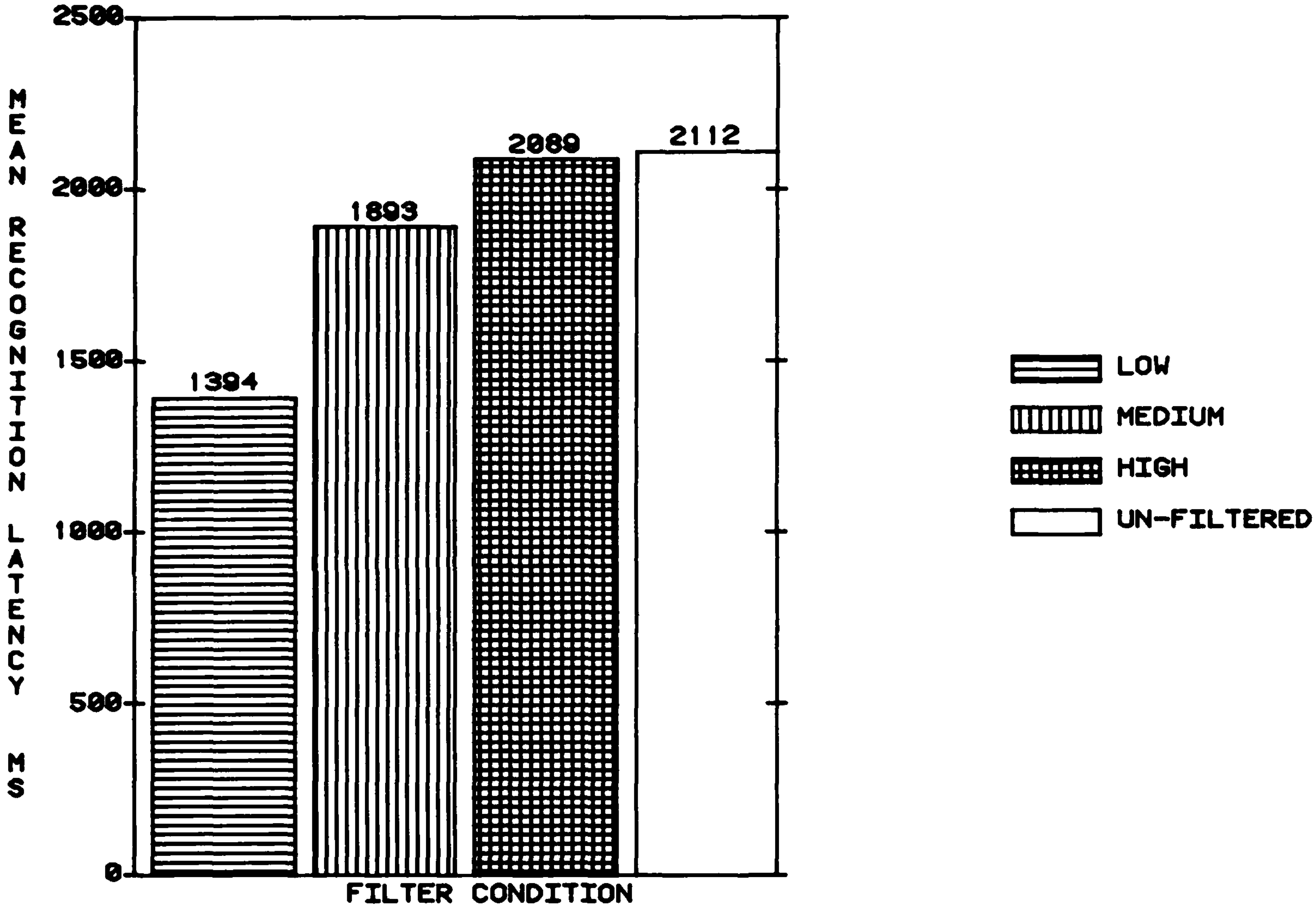


Figure 5. Mean recognition response latency for each of the four filter conditions, Experiment 1.

observers took significantly longer to respond to the mid- than to the low-frequency images even though these two conditions did not differ in accuracy.

Summary of recognition results. Overall, the recognition findings were consistent with the predictions developed in the introduction. The low- and mid-frequency images were nearly impossible to recognize reliably under the conditions presented here, whereas the high-frequency and unfiltered images led to reasonably accurate recognition levels. Furthermore, a follow-on analysis of attribute confusions indicated that neither attribute could be discriminated in the low- and mid-frequency images, the higher frequency deck structures attribute was reasonably well discriminated for only the unfiltered images (mean $d'=1.88$), and the lower frequency deck house attribute could be discriminated in both the unfiltered ($d'=2.86$) and the high-frequency imagery ($d'=1.82$). Finally, the pattern of response latencies was consistent with the accuracy analyses in suggesting that observers regarded the low-frequency images as very difficult or impossible to recognize.

Overall detection performance. The mean percentage correct detection was determined for each condition and each observer in the experiment. Since a four-alternative forced-choice detection procedure was used, unlike the overall recognition data, these data provide a bias-free index of detection performance (Green & Swets, 1966). These means are plotted by day in Figure 6 for each of the four filter conditions. A three-way (filter condition by ship by day) repeated measures ANOVA was carried out on these data. This analysis revealed significant main effects of filter, $F(3,9)=70.51$,

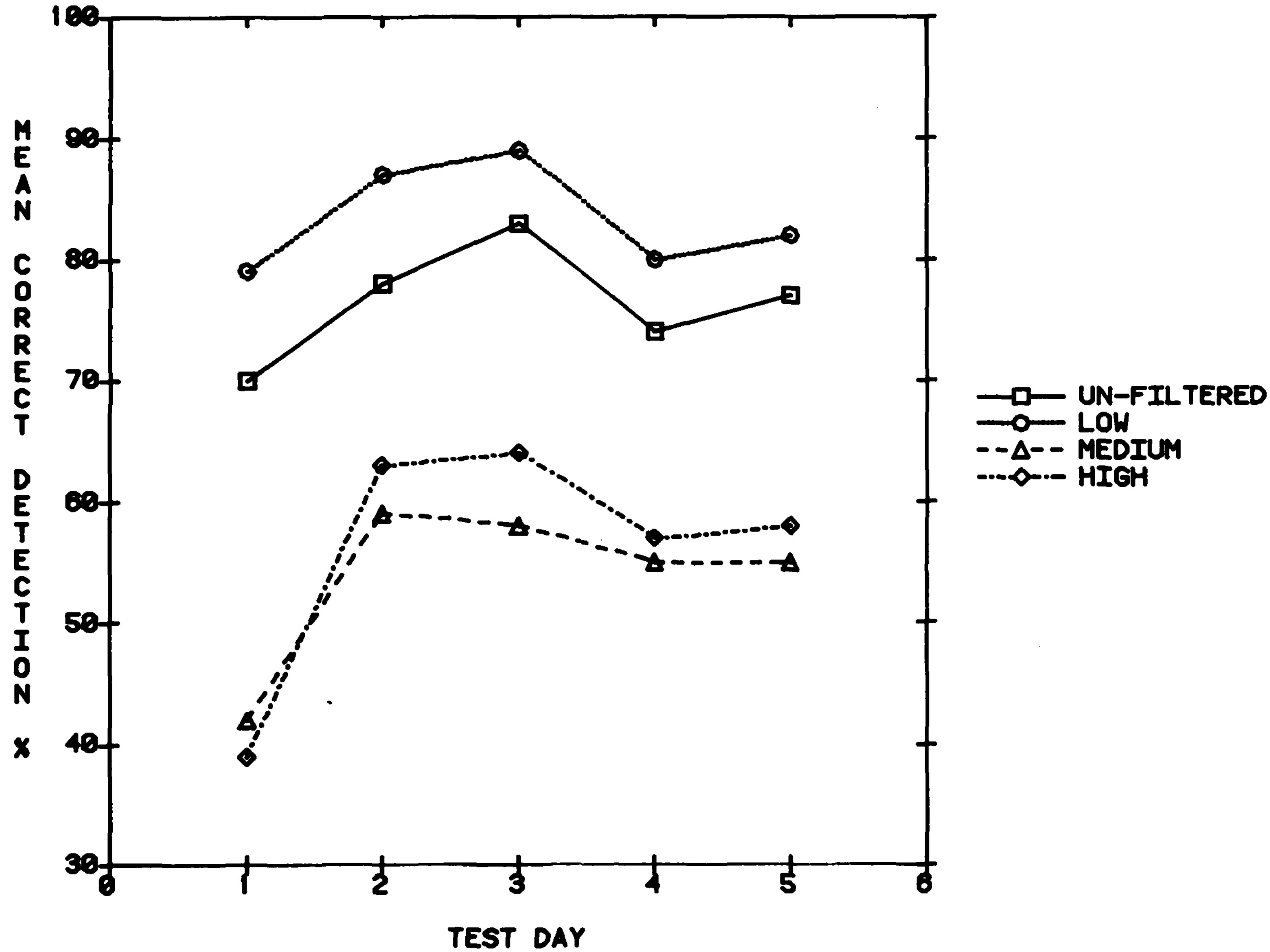


Figure 6. Mean detection performance by testing day and filter condition, Experiment 1.

$p<.001$, and ship, $F(3,9)=4.45$, $p<.05$, as well as significant filter by ship, $F(9,27)=5.66$, $p<.001$, and filter by day, $F(12,36)=3.99$, $p<.001$, interactions. The reliable main effect of ship reflects a small performance difference across the four ships (66%, 69%, 69%, and 66% for ships A, B, C, and D, respectively). This difference will not be considered further.

As seen in Figure 6, the main effect of filter condition reflects the predicted detection advantage for the low-frequency images, with performance on this condition exceeding even that for the unfiltered condition (low=83%, unfiltered=76%, high=56%, and mid=54%). However, these findings must be interpreted within the context of the two reliable interactions. Consider first the filter by day interaction depicted in Figure 6. It is obvious by visual inspection that the four filters led to a consistent pattern of performance for all except the first day when a reversal of the high- and mid-frequency conditions occurred. Since this effect is small and theoretically-uninteresting, the interaction will not be considered further.

The more important interaction occurred between filter and ship. Does this suggest that the four ships led to meaningfully different detection performance for the different filter conditions? The relevant means are shown in Table 1. A simple effects analysis revealed a highly significant main effect of filter for each of the four ships, indicating that a filter effect did occur for each of the four ships as suggested by Table 1. Furthermore, post hoc comparisons were carried out on each simple effects analysis with Duncan's Test. This revealed that both the low-frequency and

Table 1

Mean correct detection (%) by ship and filter condition.

		Filter Condition			
		Low	Mid	High	Unfilt
Ship	A	82.3	55.0	47.9	78.4
	B	84.2	55.8	54.6	80.6
	C	85.3	53.6	64.9	72.9
	D	81.4	50.6	57.5	73.6

unfiltered images were detected reliably better than the mid- and high-frequency images for all ships, but that the low-frequency condition was detected reliably better than the unfiltered images only for ship C.

In summary, detection was better for images containing low spatial frequencies (80% overall for the low-frequency and unfiltered images) than for images containing only the higher spatial frequencies (55% overall for the mid- and high-frequency images). In addition, the fact that there was a consistent tendency, statistically reliable for ship C, for the low-frequency images to produce better detection than the broad-band, unfiltered images, suggests that the presence of high spatial frequencies in the images might have interfered with the observers' ability to detect the ships.

Detection latency analysis. A mean detection response latency was determined for each individual and condition. A three-way (filter condition by ship by day) repeated measures ANOVA revealed a significant main effect of filter, $F(3,9)=5.07$, $p=.025$, and a significant filter by ship interaction, $F(9,27)=2.71$, $p=.025$. No other effects were significant at the .05 level. As in the case of the recognition latencies, inspection of the overall means for each filter condition reveals a partitioning into fast and slow responses. However, in this case the two conditions that led to accurate detection also led to fast responses (934 ms on the average) whereas those that led to poor detection (mid- and high-frequency) showed slow responding (1019 ms on the average).

Before considering these findings further, the filter by ship interaction must be considered. The relevant means as well as the *F*'s resulting from a simple effects analysis on each ship are shown in Table 2. As may be seen, a reliable simple effect of filter occurred for each of the four ships and a similar "fast/slow" pattern of latencies occurred for all but ship C. Post hoc follow-on analyses with Duncan's Test revealed (a) that the low-frequency and unfiltered image latencies did not differ for any ship, (b) that the low-frequency images were detected significantly faster than the mid- and high-frequency images for all ships, and (c) that the unfiltered images were significantly faster than the mid- and high-frequency images for only ships A and B. These latency results are consistent with the detection accuracy data in distinguishing the images with low-frequency content (the unfiltered and low-frequency images) from those with relatively little low-frequency information (the mid- and high-frequency images). Although highly speculative in the context of this experiment, it is interesting that the relatively faster response times observed for the low-frequency images is consistent with the known temporal characteristics of the low-spatial frequency channels reviewed in the introduction.

Experiment 2

The results of Experiment 1 were consistent with the attentional hypothesis on the role of spatial scale in visual perception. Different ranges of spatial frequencies led to optimal performance for the detection and recognition tasks. An additional

Table 2

Mean detection response latency (ms) by ship and filter condition.

		Filter Condition				
		Low	Mid	High	Unfilt	Mean
Ship	A	944	1027	1025	923	980
	B	913	1012	1030	937	973
	C	916	1036	982	961	974
	D	926	1027	1014	958	982
	Mean	924	1025	1013	945	

question raised by Julesz and Papathomas (1984) concerns the ability of observers to regulate the attended spatial frequency channels on a voluntary basis. Their demonstration supported what they referred to as a "strong" form of the hypothesis in revealing that some voluntary control does exist. This leads to the further question of whether, if given a choice, observers would voluntarily select imagery that had been spatially filtered to include an optimal frequency band. This question is investigated in the second experiment. In particular, the detection and recognition tasks of Experiment 1 were replicated, but in Experiment 2, observers were given control over the filter condition viewed on each trial. Immediately prior to image presentation the observer selected which of the four filter conditions to present (low-, mid-, or high-frequency dominant, or unfiltered). If the observers are sensitive to the role of spatial frequency filtering on detection and recognition performance then performance should be optimized by the selection of low-frequency images for the detection task and unfiltered images for the recognition task. This finding would suggest that individuals have a reliable "meta-perception" or intuition regarding what will contribute to good performance in a simple perceptual task (Nisbett & Wilson, 1977; Ericsson & Simon, 1980).

Method

Observers. Eight undergraduate volunteers served in the Experiment, four in the recognition task and four in the detection task. All reported normal or corrected-to-normal vision, and none

participated in Experiment 1.

Apparatus. The apparatus was identical to that used in Experiment 1.

Imagery. The imagery was identical to that used in Experiment 1.

Procedure. The procedure of Experiment 1 was used, but prior to beginning each trial the observer pressed a key to select which of the four filter conditions to observe. As a result, the frequency of occurrence of each filter condition was an additional dependent variable in this experiment. No specific instructions were given regarding which filter condition to select, observers were told simply to select the imagery which would make their task easiest. As in Experiment 1, feedback was provided following the recognition responses, and no feedback was given during detection.

Results and Discussion

Filter selection for the recognition task. The mean frequency of selection was determined for each filter condition and observer in the experiment. The results of this analysis are shown in Table 3. As is evident from the table, two of the four observers showed a decided preference for the unfiltered images, selecting these images on 97% and 66% of the trials, whereas the remaining two observers preferred the high-pass images with selection on 58% and 98% of the trials. The selection of the high-pass imagery by the latter two individuals is curious given the finding of Experiment 1 that high-pass filtered imagery led to poorer recognition performance

Table 3

Mean relative frequency of filter selection and percentage correct recognition (shown in p..rentheses) for each of four observers.

	Filter Condition			
Observer	Low	Mid	High	Unfilt
1	.12	.21	.58 (46)	.09
2	--	--	.98 (60)	--
3	.02	--	--	.97 (82)
4	.02	--	.32	.66 (88)

than did unfiltered imagery. Recognition performance is examined next.

<u>Recognition performance</u>. The mean percentage correct was determined for each preferred viewing condition for each of the four observers, collapsed across the five test sessions. These results appear in parentheses in Table 3. The two observers who showed a preference for the high-frequency imagery performed substantially poorer (53% correct) than the two with a preference for the unfiltered imagery (85% correct). This is consistent with the pattern of Experiment 1 which revealed better recognition performance for the unfiltered (69%) than for the high-frequency images (45%). Nevertheless, the overall performance levels achieved in this experiment were higher than those observed in the first experiment.

As in Experiment 1, an additional response-bias free analysis was carried out on the two by two confusion matrices for the deck-house and deck-structures attributes. The results of this analysis were consistent with those of Experiment 1 in revealing superior overall performance for the deck-house attribute (mean $\underline{d}' = 2.60$) than for the deck-structures attribute (mean $\underline{d}' = 1.72$). Furthermore, this analysis also supported the asymmetry between the two categories of observers identified above. Individuals who selected the high-frequency imagery did substantially worse on both attributes than those who selected the unfiltered imagery (deck-structures: mean $\underline{d}' = .73$ vs. 2.72; deck-house: mean $\underline{d}' = 1.86$ vs. 3.34). As in the case of the overall performance data, these analyses also show better performance for both

attributes in this experiment (mean d' = 1.72 and 2.60) than in the first experiment (mean d' = .50 and 1.39).

The key to understanding the overall differences between the results of this experiment and those of Experiment 1 may lie in the overall practice obtained under each viewing condition. Since each observer in Experiment 2 tended to select only one of the four image types for presentation, the selected type (either high-frequency or unfiltered) occurred far more frequently than in Experiment 1. In particular, individuals who selected the unfiltered imagery averaged 1579 presentations, whereas those who selected the high-frequency imagery averaged 1490 presentations. In both cases, the preferred filter condition appeared more than three times as often in this experiment than in Experiment 1. This suggests that additional practice with the selected imagery led to better overall recognition performance than found in Experiment 1.

Filter selection for the detection task. As in the case of recognition, the relative frequency of filter selection was determined for each filter condition and observer. These results are shown in Table 4. As seen in the table, each of the four observers had a clear preference for the low-pass imagery with selection for more than 90% of the trials. This finding is consistent with the results of Experiment 1 which demonstrated optimal detection performance for this filter condition. The result also stands in sharp contrast to the selection results for the recognition condition in which two of the four observers had a selection preference for a non-optimal filter.

Table 4

Mean relative frequency of filter selection and percentage correct detection (shown in parentheses) for each of four observers.

	Filter Condition			
Observer	Low	Mid	High	Unfilt
1	.87 (80)	.02	.02	.09
2	.91 (81)	--	--	.09
3	.91 (46)	.03	.03	.03
4	.95 (87)	.01	.02	.02

Detection performance. The mean percentage correct was determined for the preferred low-pass imagery for each of the four observers, collapsed across the five test sessions. These results are shown in parentheses in Table 4. With the exception of observer 3 who found the task extremely difficult, overall detection performance (74% with and 83% without Observer 3) was comparable to that obtained in Experiment 1 (83% overall). This comparability occurred despite the fact that observers in the present experiment received substantially more practice with the low-frequency imagery (mean number of trials = 1739) than did the observers in Experiment 1 (480 trials). This suggests that unlike recognition, detection levels are nearly optimal and further improvements would not be expected with more practice.

General Discussion

Overall, the results of this study are consistent with the attentional hypothesis on the role of spatial scale in image perception. In Experiment 1, different ranges of spatial frequencies led to optimal performance for the detection and recognition tasks. Experiment 2 showed further that, when given a choice, observers may not always select imagery which contains spatial frequencies which lead to optimal recognition performance. Several aspects of these results are discussed further below.

As noted above, the recognition findings were consistent with the predictions developed in the introduction. In the first experiment the unfiltered and high-frequency images were recognized substantially better than the other images. A follow-on analysis

indicated further that the higher frequency deck-structure (circular/square) was nearly impossible to discriminate in all but the unfiltered images, whereas the lower-frequency deck-house (split/full) discrimination was comparatively easy for both the high-frequency and unfiltered images. To understand this result, it is necessary to consider the spatial-frequencies involved in the two discriminations. In a simplified first analysis it can be argued that the six-pixel discrimination required to distinguish the split from full deck house would have a fundamental spatial frequency of 21.33 c/i (cycles/image) or 5.63 c/d (cycles/degree of visual angle) (128/6=21.33 c/i), whereas the three-pixel difference between the circular and square deck structures has a fundamental of 42.67 c/i or 11.26 c/d (cf. Ginsburg, 1978; p. 44). From this perspective, the observation that low- and mid-frequency images led to poor discrimination is not surprising--the information was simply not provided within the passbands of these filters to permit discrimination (.26 c/d - 2.11 c/d for low, 2.38 c/d - 8.44 c/d for mid).

However, this simplified analysis falls short of telling the whole story. For even relatively simple shapes such as those used to construct the ship images investigated here, differences between objects in the spatial frequency domain are far more subtle and complex than is suggested in the above analysis. For example, Figure 7 displays the two-dimensional Fourier transform of the difference between a circular and square shape as used in the deck-structures attribute. Examination of this figure makes it clear that the frequency-domain differences between these two simple

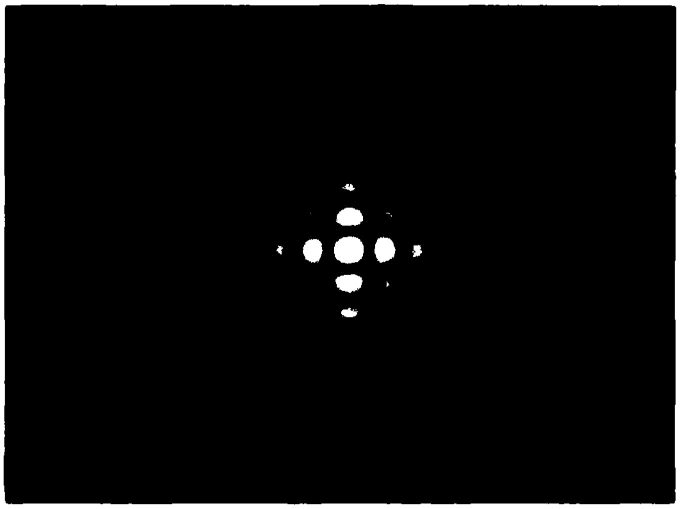


Figure 7. Log display of two-dimensional spectral magnitude data for the difference between a circle and square (as in the deck-structure attribute). The display is centered at the constant or d.c. point with spatial frequency increasing outward from this point.

shapes are broadly distributed across the spectrum. In terms of the filters used in this investigation, information sufficient for discrimination exists in all three frequency bands. The real issue, then, concerns the ability of the human observer to make use of this information.

In the first experiment observers were not able to distinguish the more subtle deck-structures attribute on the basis of a subset of spatial frequencies regardless of where these frequencies fell (i.e., low-, mid-, or high-band). Only the unfiltered images produced reliable discrimination for this attribute. This suggests that the <u>overall spectral configuration or pattern of spatial frequencies</u> is of primary importance for discrimination and hence recognition.

The results of the second experiment suggest further that substantial improvements in recognition performance can occur with additional practice. This finding must be interpreted cautiously, however, since the image selection paradigm investigated in the second experiment may have produced quite a different <u>perceptual</u> task than that investigated in the more conventional paradigm used in the first experiment. In particular, the observers in Experiment 2 were effectively classifying imagery falling within a single spatial frequency band. In contrast, observers in Experiment 1 received imagery from four spatial frequency bands (low, mid, high and unfiltered). This distinction may have permitted the former individuals to treat each of the four images (4 ships x 1 filter condition) as a unique entity to be categorized in a paired-associate fashion, whereas the observers in Experiment 1 had

the more difficult task of either learning categories for 16 unique images (4 ships x 4 filter conditions) or of determining general features or characteristics for the four ships which would apply across the various filter conditions. Additional experimentation is required to understand more fully the performance differences obtained between Experiments 1 and 2.

Detection. The detection results obtained in the present study are also consistent with the hypotheses developed in the introduction. For the luminance and exposure conditions investigated here, the low spatial frequency imagery led to unambiguously better detection performance than did imagery from the three other spatial frequency bands. Furthermore, although observers in the second experiment received considerably more practice with the low-frequency imagery than did observers in the first experiment, no overall detection performance difference occurred between the two experiments. This suggests that detection performance was nearly optimal with this imagery in both cases. Despite this, however, an alternative to the attentional hypothesis can be proposed to account for the detection results. Specifically, the 1 cycle/degree center frequency of the low-pass spatial frequency filters investigated here would be expected to yield maximum contrast sensitivity at the low luminance levels used (Campbell & Robson, 1968). This alone could account for the superior detection performance observed for this filter condition. More interesting, however, is the finding that overall detection was better for the low frequency (83% correct) than for the unfiltered (76%) imagery despite the fact that the unfiltered imagery obviously

contains the low frequency information. As indicated previously, this suggests a possible interference effect of the higher frequency information contained in the original, unfiltered imagery. As in the case of recognition, this underscores the importance of the overall pattern of spatial frequencies for detection performance.

Implications for image processing and image quality metrics. Image processing and enhancement techniques are widely used in Navy applications such as reconnaissance, weather forcasting, and sonar imaging. In many such applications, a human observer is required to apply image enhancement algorithms on an interactive basis to improve image quality for the task at hand. Two aspects of this problem deserve further comment in light of the findings reported here, the role of the human observer in interaction, and the perceptual basis for assessing image quality.

First, the present study was only part of a larger project to investigate human-computer interaction in image processing and was not designed to examine fully-interactive capabilities. Despite this, however, a limited "interactive" capability was provided in Experiment 2 when observers were required to select which of four spatial frequency filter conditions to observe on each trial--a first step in the investigation of fully-interactive systems. The results of this experiment revealed that some observers did not select the optimal spatial frequency parameters for image recognition. Additional research is called for on the problem of determining what an observer knows of the conditions that will lead to optimal performance. Previous research by Peterson, Goppelt, & Grossman (1984) has shown that spatial frequency filtering can lead

to improved recognition performance for infrared ship images. The results reported here suggest that observers may not be able to take advantage of such image processing tools in an interactive imaging environment without some kind of additional decision aid or expert system to assist them.

Second, image "quality" has received considerable attention in the image processing literature (Snyder, Shedivy, & Maddox, 1982). The objective of image quality research is to determine a scale or metric of image quality suitable for predicting the ability of observers to extract information from images. Although not designed to investigate this problem, the findings of the present study suggest that singular measures of image quality necessarily fail to capture the perceptual complexity of imagery for all tasks. For example, one could argue that the low-pass imagery provided very high quality for detection but low quality for recognition, whereas the reverse was true for recognition. No simple measure can provide an accurate sense of image quality without considering the observer's task. Additional work such as that carried out by Kuperman (1985) is needed to place image quality metrics on a more secure theoretical footing.

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